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Toward a Pragmatic Theory for Managing Nescience

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Aristotle's dictum *scio nescio* (I know that I don't know) may serve as a source of enhanced performance for organizations. Awareness of nescience sets the direction for further inquiry, as managers tend to move in the direction that they believe will reduce nescience most. However, nescience is difficult to quantify, so, to date, managers have primarily relied on intuition. This paper introduces a theoretical framework for managing nescience that is based on information theory. This framework is tested in three exploratory empirical studies that take place in highly contrasting settings: semiconductor manufacturing, medical diagnostics and social media analytics. All three studies demonstrate that metrics related to information entropy can be used to quantify nescience. However, practitioners value the framework and its metrics more highly in the settings where the quality of or access to information drives successful product development. The problems encountered in these settings tended to be well-structured, or they were converted from being ill-structured to being well-structured. Further study of more highly contrasting practical settings will be required to determine whether frameworks based on information theory can serve as foundations for a broadly based, pragmatic theory for managing nescience.

Keywords: Quantifying nescience; information theory; entropy; semiconductor manufacturing; medical diagnostics; social network analysis; analytics.

1. Introduction

Aristotle's dictum *scio nescio* (I know that I don't know) may serve as a source of enhanced performance for organizations. Awareness of nescience sets the direction

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for further inquiry, as managers tend to move in the direction that they believe will reduce nescience most [Hasenauer (2015)]. However, nescience is difficult to quantify, so, to date, managers have primarily relied on intuition to decide where inquiry should go next.

The purpose of this paper is to investigate whether nescience can be quantified in a manner that is of value to practicing managers in industry. The paper proposes a theoretical framework for managing nescience that is based on information theory. The paper consequently addresses the following research question: Can information theory act as a theoretical foundation for managing nescience in a practical setting? The paper subsequently presents three exploratory studies, which investigate how nescience is managed in three highly contrasting industrial settings. The first study scrutinizes fault reduction and yield management practices in semiconductor manufacturing and process development. The second study examines automated diagnosis of osteoarthritis. The third researches how a social media analytics firm identifies key influencers within the market space of one of its clients.[a] In all three studies, entropy-based metrics that the framework provides were applicable to managing nescience, implicitly in the case of semiconductor manufacturing but very explicitly in medical diagnostics and social media analytics. Approaches based on information theory were considered particularly valuable in the medical diagnostics and social network analytics studies, where they comprised a key aspect of the core technologies of the products and services that were under development. Thus, the theoretical framework presented in this paper can be considered highly pragmatic in the sense of Peirce [1878] and James [1907], at least in the two studies in which it definitely "works."

The limitations of the theoretical framework presented in this paper can primarily be derived from context. From the point of view of management practice, the framework "worked well" in settings like medical diagnostics and social network analysis, where successful product/service development is driven by the quality of information [Ljuhar (2016); Ljuhar *et al.* (2016)] and by access to information, respectively. Problems encountered in these settings were considered well-structured [Pople (1982); Reitman (1965); Simon (1973)], or they could be converted from being ill-structured to being well-structured. By contrast, practitioners did not deploy the framework in semiconductor manufacturing and process development, even though entropy-based metrics characterize key aspects of the problem-solving process in that industry quite well [Weber *et al.* (2002)]. The semiconductor industry is driven by urgency [Leachman and Ding (2007)], yield [Bohn and Terwiesch (1999)] and capital productivity [Silverman (1994)], and the practitioners observed in that setting were persistently confronted with problems that were ill-structured.

The primary contribution of this paper consists of developing a theoretical framework that quantifies nescience and testing that framework in the three exploratory studies that take place in highly contrasting industrial settings. Moving toward a more generalizable, pragmatic theory of nescience will involve further

[a] Preliminary results of the research described in this paper have been presented in Weber *et al.* [2017]. This paper presents additional empirical findings and theoretical arguments.

research that assesses the normative value of the framework presented in this paper. In that research, the investigators will have to determine whether the framework "works" or "does not work" from the point of view management practice in a multitude of different settings. Specifically, will managers, who claim to be pragmatists when asked about their management philosophy [Spender (1996)], ascribe "*cash value*" [James (1907)] to the theoretical framework proposed in this paper?

2. Background

Significant theoretical work on nescience has already been done. For example, Shackle [1983] proposes that economic activity cannot be managed in totality because of "unknowledge" of the future. He believes that individuals (and managers in particular) continuously have to make choices whose consequences they do not understand. Yet, making a choice, or even not making it, has inherent consequences in itself. These choices influence downstream choices that could be made in the future by the individual him/herself or by other individuals. However, *a priori*, it is impossible to know for certain when these choices have to be made or what the nature of these choices will be.

García-Leiva [2018] differentiates between "nescience" and "ignorance". Both words are traditionally defined as "a lack of knowledge or awareness." However, García-Leiva argues that subtle differences in meaning appear, when choice is introduced into the definition of these terms.

> "Ignorance refers to the lack of knowledge when knowledge is there (we do not know but we could do so, for example, by reading a book), and nescience refers to the lack of knowledge when knowledge is not there (we do not know, and it is not possible to know, since nobody knows)." [García-Leiva (2018, p. 19)]

García-Leiva divides the unknown into two parts: the *known unknown* and the *unknown unknown* [García-Leiva (2018, p. 26)]. He refers to the known unknown as known problems for which no solution has been found. By contrast, he defines the unknown unknown as a set of problems that has not even been identified. For example, the author considers diabetes part of the known unknown, because we know what diabetes is and we are aware that nobody knows how to cure it. However, AIDS in the 1960s would have been part of the unknown unknown to the medical establishment, because at that time the complex of phenomena associated with AIDS had not yet been observed by the medical establishment. AIDS has since become part of the known unknown. While there is no cure for the syndrome yet, the phenomena with which AIDS is associated are observed regularly and studied intensely. For both ailments, research directions are generally set by what we know that we don't know.

Klein [2001] argues that knowledge and nescience are two sides of the same coin, which, in conjunction, act as the engine for science and innovation when they are integrated properly. In practice, the challenges to managing knowledge come from what is partially unknown rather than totally unknown. Klein lists a series of approaches for managing what he terms "fuzzy knowledge" [Klein (2001, pp. 7–8)], which include heuristics [e.g. Gigerenzer and Todd (1999)], intuition, dialog/communication, scenario management [e.g. Graf (1999)], systems thinking [e.g. Senge (1990)] and learning by experience. These "instruments of knowledge" catalyze innovation and make knowledge about nescience productive. They are ideally suited to make knowledge actionable, especially in times of information overload. They encourage organizational learning, and they optimize the "knowledge efficiency" of employees. Fuzzy Knowledge Management, as defined by Klein [2001], provides a foundation for acting flexibly and remaining decisive in complex situations. It also successfully secures productivity and innovation within an enterprise, thereby enhancing the enterprise's competitiveness.

The concept of nescience may have broadly based applications pertaining to problem solving, which relies heavily on iterative trial-and-error processes [Baron (1988, pp. 43–47)], especially if the problems to be solved are of a technical nature [Allen (1966); Marples (1961)]. (Iterative trial-and-error has also been identified as a significant attribute of learning by doing [Arrow (1962)], learning by using [Rosenberg (1982)], learning before doing [Pisano (1996)], design [Alexander (1964); Simon (1981); Smith and Eppinger (1997a,b); Wheelwright and Clark (1992)] and experimentation [Adler and Clark (1991); Bohn (1995); Iansiti and West (1997); Pisano (1996); Thomke (1998)], which are all cognitive organizational phenomena that prominently depend on problem-solving practices.) If one can precisely specify a trial-and-error process that will lead to a desired solution of the problem in a practical amount of time, then the problem is considered well-structured [Pople (1982); Reitman (1965); Simon (1973)]. The problem solver can then partition a problem's "solution space" — the domain in which the problem's solution is known to lie — until the problem is solved [von Hippel (1990)]. Essentially, the problem solver reduces nescience about the problem until nescience is no more. If trial-and-error approaches provide no clear path to a solution on their own, then the problem is considered ill-structured [Pople (1982); Reitman (1965); Simon (1973)].

Schatten *et al.* [2003] argue that progress in a knowledge society depends upon the creation and dissemination of new knowledge. However, nescience, insecurity and system complexity in general increase as knowledge is created and applied. New problems arise, and systemic risk increases as a consequence [Füllsack (2002); Willke (2002)]. Thus, the problem of managing nescience can be viewed as ontological in the sense of Nonaka [1994]. Nescience increases as the spiral of knowledge creation (socialization, externalization, combination, and internalization) involves an ever-increasing part of an organization. This phenomenon has arguably resulted in a crisis in knowledge management. As Stewart and colleagues point out: "Unfortunately, contemporary technology for knowledge management is a hodgepodge of executive IS, group-support systems, intranets, decision support systems, and knowledge-based systems" [Stewart *et al.* (2000)] as cited on p. 1 of Schatten *et al.* (2003)]. Problems with acceptance by end users consequently arise.

Schatten *et al.* [2003] have accepted the fact that a growing knowledge base inherently increases nescience, and that managing nescience is central to an organization's success. The authors intend to close the gap between nescience and knowledge management by integrating all roles of knowledge management — the project user, the administrator, the project manager, the software system and intelligent agent — into the existing communications infrastructure. They propose a question-related system, which establishes a need for answers and enables a market for knowledge. They suggest that experts donate knowledge that they perceive to be of greatest value to their user community. The true value of the knowledge can be determined by monitoring the activities of the information seekers and the experts themselves. User satisfaction and frequency of access are indicators of how efficient and effective the KM system actually is [Schatten *et al.* (2003, p. 1)].

All the above approaches would be improved upon, if a theory that quantifies nescience could be developed, and if nescience could be measured directly. Under these circumstances, managers could set policy in a direction that yields the greatest reduction of nescience. For example, research projects could be chosen by the how much they reduce nescience. More generally, managers could use nescience as a criterion for setting priorities for problem solving and scenario planning [e.g. Derbyshire (2017)]. Problems, whose solutions appear to reduce nescience the most, would be attacked first.

García-Leiva's is working on a book whose goal is to describe in detail "the Theory of Nescience, a new mathematical theory that has been developed with the aim of quantitatively measuring how much we do not know" [García-Leiva (2018, p. 13)]. The author relies on concepts from the mathematical sciences that underlie computer science (discrete mathematics, computability, coding, complexity and minimum length) to establish the principles of nescience. He also identifies subjects to which this theory could be applied [García-Leiva (2018, Chaps. 9–13)]. Potential applications include the scientific method and the evolution of knowledge, as well as identifying new research topics, interesting research questions and potentially lucrative business opportunities. The author also contends that the theory has applications in software engineering and quantum computing.

Unfortunately, to date, very little empirical work on managing nescience has been done. Thus, the abovementioned theories have not been validated. These theories also tend to be rather complex, which has prevented them from being applied in practice. What is needed is a pragmatic, relatively simple theory of nescience, to which managers can ascribe value [e.g. James (1907); Peirce (1878)]. Such a theory would have to include quantifiable metrics for nescience. Managers would also have to be able to put this theory into practice without engaging in extensive philosophical debates.

3. Theoretical Framework

In this section, we present a theoretical framework, which moves the state of the art that was summarized in the previous section toward a more pragmatic theory of nescience. This framework is not nearly as involved as what has been presented in prior art [e.g. Antoniou (2013); García-Leiva (2018); Klein (2001); Natsikos and Richter (2011); Schatten *et al.* (2003); Schneider (2007); Shackle (1955); Willke (2002)]. Instead, it is based upon well-known principles of information theory [e.g. Abramson (1963); Beckmann (1967); Hartley (1928); Kullback (1968)], which can be implemented in industrial settings much more readily. The framework follows Shannon and Weaver's [1949] view that knowledge is certain information in the sense of, "I ***know*** this to be absolutely true." It provides the following metrics through which nescience can be quantified [Weber *et al.* (2002), pp. 411–412)]:

"A source of information reveals an amount of information $I(X_i)$ whenever the source is in state X_i. $I(X_i)$ is therefore known as the ***self-information*** and is given by

$$I(X_i) = -\log_{10} P(X_i) \quad \text{hartleys}, \tag{1}$$

where $P(X_i)$ is[b] the probability of occurrence of state X_i. ***Information entropy*** is defined as the expectation of $I(X_i)$, or the average amount of self-information per state [Shannon and Weaver (1949)]. It is given by the random variable

$$\begin{aligned} H(X_i)_{i=1} &= \langle I(X_i)\rangle = \sum^{m} P(X_i) I(X_i), \\ &= -\sum_{i=1}^{m} P(X_i)\log_{10} P(X_i) \quad \text{hartleys/state.''} \end{aligned} \tag{2}$$

Information entropy is at a maximum when all states are equiprobable or $P(X_i) = 1/m$, a situation that reflects minimum knowledge, maximum uncertainty and maximum nescience about the information source. Information entropy, and thus nescience, decreases from its maximum value as $P(X_i)$ concentrates into fewer states. Information entropy, and thus nescience, approaches zero as the probability of one state approaches unity, and the probability of all other states approach zero. In other words, information entropy and nescience approach naught as the probability of an event occurring in a specific state approaches unity. The relative entropy can thus be used to compare the nescience of the final state of an experimentation cycle to the nescience of its initial state. It can also be used to benchmark the amount of information extracted by or nescience reduced by two different, possibly unrelated experiments. Furthermore, approaches that reduce nescience by decreasing information entropy can provide guidance to machine intelligence. For example, diagnostic tools can increase the efficiency of their searches for anomalies by proceeding in a direction that reduces entropy the most [e.g. Ljuhar (2016); Ljuhar *et al.* (2016); Rocha *et al.* (2008); Weber *et al.* (2017)].

Approaches that utilize information theory to quantify nescience can accommodate network effects [e.g. Nikolaev *et al.* (2015); Tutzauer (2007)]. For example, entropy-based centrality identifies specific loci within a network at which information is highly concentrated, whereas entropy centralization quantifies the concentration of information across the whole network [Mayande and Weber (2011)]. Entropy-based centrality for information flow for all shortest paths (geodesics) between a node v_i and all other nodes in the network v_j is given by

$$H_i = \sum_{j=1}^{n-1} P_{i,j} \log P_{i,j}, \tag{3}$$

[b] The base of $\log P(X_i)$ determines the units of information. The binary $\log_2 P(X_i)$ is given in "bits"; the decimal $\log_{10} P(X_i)$ is given in "hartleys"; and the natural $\log_e P(X_i)$ is expressed in "nats".

where $i \neq j$, where n denotes the total number of nodes in the network, and where $P_{i,j}$ represents the probability that information flows between v_i and v_j. The total entropy centrality for geodesic serial flow, or entropy centralization across the whole network, is given by

$$H_T = \sum_{i=1}^{n} H_i. \tag{4}$$

Progress toward a pragmatic, entropy-based theory of nescience can be made by conducting research, which looks at the phenomenon from the point of view of managerial practice in industry. Such research could consist of a quantitative analysis of how nescience in its various forms affects organizational performance or a qualitative analysis of the processes through which nescience is reduced [Zenobia and Weber (2012)]. Even a simple documentation of how entropy-based measures of nescience can be applied in industry would help advance the cause of further study or further application of the approaches discussed above.

4. Research Methods

To test the theoretical framework from the previous section, the authors of this paper conducted three exploratory studies of how three different organizations that operate in three different industrial settings manage nescience. The technical literature that pertains to each setting indicates that approaches to managing nescience that are based on information theory are potentially applicable in all three settings. The three specific settings under study were chosen for their contrasting economic environments, so that any commonality that emerges from the studies would enhance the generalizability of the proposed theoretical framework. The host firms of two of the studies did not grant permission to be named explicitly; instead, they are identified via aliases.

The semiconductor manufacturing study was conducted in the integrated circuit (IC) division, henceforth identified as Semorg, of a very large manufacturer of computer and electronic products, henceforth referred to as Comptron. Semorg consisted of an R&D facility and multiple manufacturing sites, all located in the Western United States. Comptron has been involved in IC manufacturing and semiconductor process development since the 1960s. The firm's total annual revenue exceeded US$ 10 billion throughout the duration of the study, of which slightly less than $1 billion could be attributed to the efforts of Semorg.

Leading-edge semiconductor integrated circuit manufacturers operate in an urgent environment [Gersick (1988); Terwiesch and Bohn (2001)] in which the unit price of the IC's to be sold erodes over time [Leachman and Ding (2007); Weber (2004, 2013)] and the objective of problem solving — rapid improvement of quality — is clear to essentially everyone in the industry [Weber (2002)]. Thus, the solution-spaces of problems related to semiconductor manufacturing are relatively well defined, but they need to be partitioned rapidly to avoid major loss of revenue [Leachman and Ding (2007); Weber (2002, 2004, 2013)]. The key to this partitioning is rapid concentration of information [Weber *et al.* (2002)].

The osteoarthritis study was conducted at Braincon Technologies (in Vienna, Austria), a consortium of technology firms that are active in industries related to health care [Ljuhar (2016)]. Braincon was founded in 1992. It acts as a wholesaler, developer and solutions provider in diverse fields such as radiology, medical imaging and medical hygiene technologies. Given that Braincon never employed more than 15 people at any particular time, it has to be considered a small enterprise.

The solution spaces of problems pertaining to automated diagnosis of osteoarthritis are sufficiently well defined for automated diagnosis to be attempted, because problems of interest tend to manifest themselves near the surface of bones [e.g. Benhamou *et al.* (1994); Pothaud *et al.* (1998); Rocha *et al.* (2008)]. The primary motivation for automated diagnosis is early, more accurate detection of osteoarthritis, which leads to fewer invasive surgical procedures and less human suffering [Ljuhar (2016); Ljuhar *et al.* (2016)]. Cost and speed of diagnosis are also considered as issues, but they are not the driving factors [Ljuhar (2016); Ljuhar *et al.* (2016)]. Thus, it is important to partition the solution space (concentrate information) accurately, rather than speedily.

The social network analysis study documents how a social media analytics firm, codenamed SMAF in this paper, finds potential clients in cyberspace for Xilinx, a Silicon-Valley-based semiconductor firm that primarily produces floating point gate arrays (FPGAs). SMAF was founded in 2011, and about $5 million have been invested in SMAF to date. SMAF has never employed more than 6 people at any particular time. Thus, it has to be considered a small startup firm. In the study that was conducted for this paper, SMAF's primary motivation was generating revenue for Xilinx through discovery.

The economic environment of the social network analytics study is not particularly urgent, but the solution space for the problem that SMAF addresses is not well-defined. The problem contains a high degree of ambiguity [Schrader *et al.* (1993)], because initially SMAF does not really know where to look and for what it should be looking. In other words, the degree of nescience is very high, but nobody knows how high. Nonetheless, the proposed framework could be relevant, because the analytics firm used information flows as guideposts for it analysis.

The arguments made in this paper are primarily based on participative action research [Chevalier and Buckles (2013); Reason and Bradbury (2008); Whyte (1991)], where one of the authors was directly involved as a researcher and a practitioner in one study. The authors performed a variety of different roles in their respective settings during their period of involvement, including planner, leader, catalyzer, facilitator, teacher, designer, listener, observer, synthesizer and reporter [O'Brien (1998)]. The intent was to produce a mutually agreeable outcome for all participants [O'Brien (1998)].

All three studies in this paper transpired over prolonged periods of time: the semiconductor manufacturing study from 1996 to 2016; the medical diagnostics study from 2013 to 2017; and the social network analytics study from 2011 to 2015. As required by O'Brien [1998], at the end of each study, all participants and stakeholders were able to take responsibility for and maintain all processes and practices that were developed in conjunction with the authors of this paper. Thus, at the end of each study, the participants were able to "effect desired change as a path to generating knowledge and empowering stakeholders" [Bradbury-Huang (2010, p. 93)].

Direct observation of the participants by the authors at the three firms under study constituted the primary source of data for the three studies in this paper. Secondary sources include evidence derived from papers in the academic literature, presentations at practitioners' conferences and 104 retrospective, semi-structured interviews. The respondents in the secondary source interviews were recruited by snowball sampling. They were employed by 30 firms in the industries under study, not just the firms under observation. The respondents tended to be technologists, technology managers and entrepreneurs who were considered experts in the practices under study. Audio and video recordings of interviews and of practitioners in action were prohibited for reasons of confidentiality; data from primary sources and interviews were recorded in writing by the researchers.

In their observations and interviews, the researchers specifically watched for data pertaining to variables that are associated with concentration of information, timing, benefits and costs. Variables pertaining to information included the number locations — physical or virtual — in which a problem could lie [von Hippel (1990)], as well as the odds of a problem being found in a particular location. Issues of timing typically pertained to when a problem was first identified and when it was solved. Benefits and costs could be financial (as in revenue gained or reduced cash outlays) or human (as in better odds of correct diagnosis or whether a surgical procedure could be avoided).

Data analysis consisted of identifying associations between the variables under consideration. Theoretical constructs were built from these associations and validated in interviews with participants. A construct was considered as validated, if the participants considered it useful or valuable in practice. In their interviews with secondary sources, the researchers did not ask any questions from which quantitative data could be elicited. Thus, none of the conclusions from this paper carry statistical significance.

5. Finding Faults in Semiconductor Manufacturing

As it does in most industries with a large underlying knowledge base [Pisano (1996)], success in leading-edge IC manufacturing, to a large degree, depends upon rapid and early learning [Leachman and Ding (2007); Weber (2004, 2013)] in which problems need to be solved as rapidly and early as possible for an IC venture to remain profitable [Weber (2002)]. In other words, IC manufacturing is characterized by radical experience curves [Weber (2006)]. Once a semiconductor process is producing parts that can be sold, competitive advantage shifts to capital productivity [Silverman (1994)]; [Weber and Yang (2012, 2014, 2016)]. The IC manufacturer needs to amortize the billions of dollars of plant equipment effectively. A yield problem can easily cost \$20,000 per minute [Weber (2002)] in the form of idle equipment or revenue loss. Thus, it needs to be diagnosed and treated within the shortest possible time. This pattern was clearly observed at Semorg and confirmed by secondary sources.

Yield learning [Stapper and Rosner (1995); Weber (2004, 2013)] and yield maintenance [Weber (2002)] are particularly important in semiconductor manufacturing, because semiconductor manufacturing is a yield-driven industry [Bohn and Terwiesch (1999)]. Yield learning and yield maintenance involves iterative experimentation processes, which are repeated until all sources of yield loss are detected, identified and eliminated, or until the cost of further experimentation exceeds the benefit of the knowledge gained [Thomke (1998)]. Experimentation consists of diagnosing electrical faults that cause yield loss (such as the defect in Fig. 1), localizing their source within the manufacturing process, precisely identifying the root cause, designing a solution for the problem, implementing the solution, and assessing its impact on the manufacturing process as a whole [Weber (2002); Weber *et al.* (2002)]. Localization has been the most time-consuming step in this process [Weber (2002)]. Accelerating problem localization consequently constitutes the most lucrative proposition pertaining to problem solving in an urgent and capital-intensive environment [Weber *et al.* (2002)].

Problem localization can be accelerated in one of two ways: (1) by designing an experiment that extracts more information per experimentation cycle or (2) by shortening the experimentation cycle. Semiconductor manufacturers achieve the former by designing experiments that look at the complete process [Bohn (1995, p. 33)]. They accomplish the latter by designing short-cycle experiments [e.g. Weber (1992); Wein (1991)]. Essentially, the question is, how do we reduce nescience the most rapidly? Do we eliminate more nescience by designing a more comprehensive experiment that runs on a longer cycle or by performing a sequence of head-to-tail experiments with shorter cycles that reveal less information in the aggregate?

An effective yield learning strategy consists of striking a balance between these approaches [Weber *et al.* (1995)], whatever said balance may be. However, to execute such a strategy optimally and predictably, an IC manufacturer needs to quantify nescience, or at least approximate it. Then, yield learning becomes yield management, a set of practices that allows IC manufacturers to deliver on schedules that have been devised years in advance [Stapper and Rosner (1995); Weber (2004, 2013); Weber *et al.* (1995); Weber and Yang (2012); Yang *et al.* (2013)].

In general, the problem-localization process proceeds in the following manner. A product on a production lot is defective when it exits the fabrication facility (fab), i.e. it contains an electrical fault. Failure analysis practices identify potential causes of the fault, and suggest general areas within the manufacturing process in which the problem may reside. The challenge is to identify the specific process step that contains the source of the problem as rapidly as possible. Yield analysis engineers subsequently design short-cycle experiments that explore the regions of potential trouble. These experiments reduce nescience by partitioning the solution space of the problem. The more rapidly they do so, the better for the bottom line of the IC manufacturer.

Unfortunately, experimentation is not for free [Loch *et al.* (2001)], and the cost of an experiment in modern IC manufacturing is particularly high. An experiment that consists of a lot of 12 wafers may cost as much as $10,000 to conduct, and, due to a high degree of process noise in semiconductor manufacturing [Bohn (1995)], it would

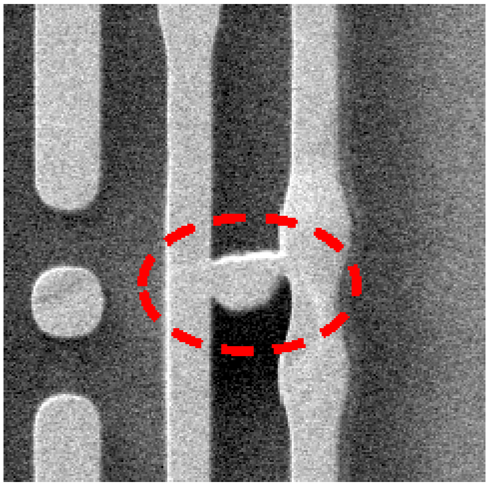


Fig. 1. A physical defect in an integrated circuit interconnect layer that is likely to cause an electrical fault (Courtesy: Applied Materials Corporation).

have to be repeated many times for its conclusion to be valid. Experiments consequently need to be conducted parsimoniously. Only experiments that reduce nescience dramatically within a short time should be performed.

In order to determine which experiments should be performed, Weber *et al.* [2002] developed a method to measure the effectiveness of problem-solving practices, which is based on information entropy as characterized in Eq. (2). If a state "i" in (2) represents a particular process step within an IC manufacturing process, X_i constitutes the event that a fault resides within "i", and $P(X_i)$ denotes the probability of a fault (event) occurring in X_i, then $H(X_i)$ can act as a proxy for nescience for problem localization in IC manufacturing. Information entropy, like nescience, decreases as uncertainty with respect to the location of the fault decreases. If $H(X_i) = 0$, then the defect is caused by a specific process step with absolute certainty, and nescience (entropy) with respect to location has been reduced to naught. The relative entropy can thus be used to compare the degree of localization at the end of an experiment cycle to that of its initial state. It can also be used benchmark the degree of localization achieved by or nescience reduced by two different experiments.

The stylized example in Fig. 2 illustrates how this works in an IC manufacturing process that consists of 500 process steps. A batch (silicon wafer) of integrated circuits has emerged from the production line. It contains a multitude of faults, which failure analysis procedures at the end of the line have localized to process steps $X_{101} - X_{110}$. The source of the faults needs to be localized down to the individual process step for corrective action to be taken. This is the job of the yield analysis engineers.

Before they launch an experiment that localizes the source of the fault further, the yield analysis engineers have no information as to which of the 10 process steps in question contains the fault. This situation, equiprobability over $X_{101} - X_{110}$, is given

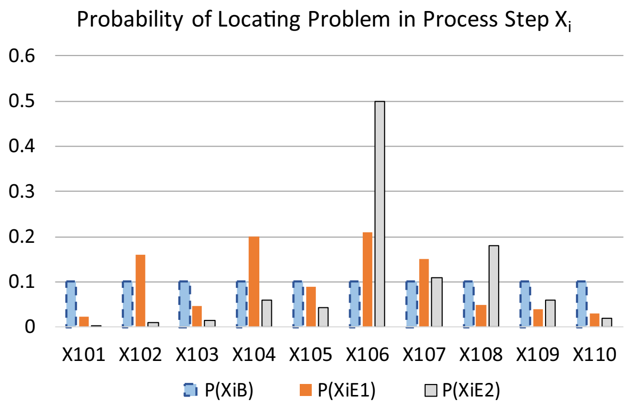


Fig. 2. Probability distributions of a fault occurring in process steps $X_{101} - X_{110}$.

Table 1. Comparing information entropies (in hartleys per process step) to localize electrical faults in integrated circuits.

$H(X_{iB})$	$H(X_{iE1})$	$H(X_{iE2})$	$H(X_{iE1})$–$H(X_{iB})$	$H(X_{iE2})$–$H(X_{iB})$
1.000	0.893	0.681	−0.107	−0.319

by the probability distribution $P(X_{iB})$ in Fig. 2. (All probabilities not shown in Fig. 2 equal naught.) The yield analysis engineers have the option of launching two experiments: E1 and E2. It is estimated that launching E1 will result in the probability distribution $P(X_{iE_1})$, whereas launching E2 will result in the probability distribution $P(X_{iE_2})$. Which of these experiments do the yield engineers launch?

Table 1 shows that comparing information entropies provides the answer. Conducting experiment E1 reduces entropy (nescience) by 0.107 hartleys per process step; conducting E2 reduces entropy (nescience) 0.319 hartleys per process step. Thus, *ceteris paribus* (all else being equal), experiment E2 is preferable to experiment E1 from the point of view of localizing an electrical fault because it reduces nescience to a greater degree.

Unfortunately, all else is not equal in IC manufacturing, an industry that is driven by yield, urgency and capital productivity. E2 could be costlier to conduct than E1, driving up the total cost of ownership of E1 [e.g. Dance, DiFloria and Jimenez (1996); Martinez *et al.* (1992); Secrest and Burggraaf (1993)]. E2 could also have a longer experimentation cycle than E1, which would diminish the value of E2 by taking up extra time [Leachman and Ding (2007); Terwiesch and Bohn (2001); Weber (2002, 2004, 2006, 2013)].

Mathematical models for trading off cost and value of experiments have been developed [Leachman and Ding (2007); Terwiesch and Bohn (2001); Weber (2002, 2004, 2006, 2013)] and validated in IC manufacturing [Leachman and Ding (2007)]. (One approach even uses information theory to quantify the value of ownership of yield analysis technologies [Weber *et al.* (2002)]). However, limitations pertaining to problem structure have prevented their implementation on a large scale. Many of technical problems in IC manufacturing are ill-structured [Baron (1988);

Pople (1982); Reitman (1965); Simon (1973); von Hippel (1990)] because they are characterized by ambiguity, as well as by uncertainty [Schrader *et al.* (1993)]. Thus, their solution space cannot really be defined, and trial-and-error procedures cannot really be implemented successfully.

In practice, the economic environment of IC manufacturing is so urgent that IC manufacturers do not choose between one experiment and the other. They have to conduct a multitude of experiments in parallel [Weber (1992)] to minimize the loss of revenue that yield problems can cause [Bohn and Terwiesch (1999); Leachman and Ding (2007); Weber (2002, 2004, 2006, 2013)]. Thus, experimentation capacity becomes a constraint on profitability and a source of competitive advantage [Iansiti and West (1997)]. The approach described in this section is consequently rarely used to differentiate between one experiment and the other, even though the entropy metrics that it deploys characterize nescience quite well. Instead, the approach can be used to discriminate between experiments that are worth conducting in an environment characterized by constrained experimentation capacity, and other experiments that are not.

6. Braincon Technologies: Predictive Diagnosis of Osteoarthritis (OA)

Osteoarthritis (OA) is the most common form of arthritis and a major cause of disability [Bijlsma *et al.* (2011)]. The most prevalent OA localization is the knee joint, affecting 24% of the general population [Pereira *et al.* (2011)]. Assessment of knee-OA usually involves anterior, posterior and lateral radiographs to evaluate medial/lateral joint spaces, osteophytes, sclerosis and joint deformation [Benhamou *et al.* (1994)]. Such assessments are based on visual examination and grading of radiographs by the individual physician using the Kellgren–Lawrence (KL) score [Kellgren and Lawrence (1957)]. However, subjective parameter grading, perspective errors and low reproducibility are limiting factors when assessing for OA. In addition, a study has shown that the single KL score agreement rate among three physicians can be as low as 15% [Ljuhar *et al.* (2016)]. Moreover, OA assessments based on visual radiographic parameter grading have limited capabilities when investigating the early onset of OA.

A potential solution to these shortcomings can be found in the assessment of selected regions of interest (ROIs) of the trabecular bone which provide significant information on the status of OA. Studies in the medical community have shown that local bone degradations caused by OA can be assessed by means of fractal analysis of X-ray images. Such degradations affect in particular the subchondral/subarticular area of the tibia (the tibia being the bone at bottom of the knee joint). The assessment of bone surface roughness of the trabecular bone structure seems to be a strong indicator of potential early signs of disease presence and progression [e.g. Benhamou *et al.* (1994); Pothaud *et al.* (1998); Rocha *et al.* (2008)].

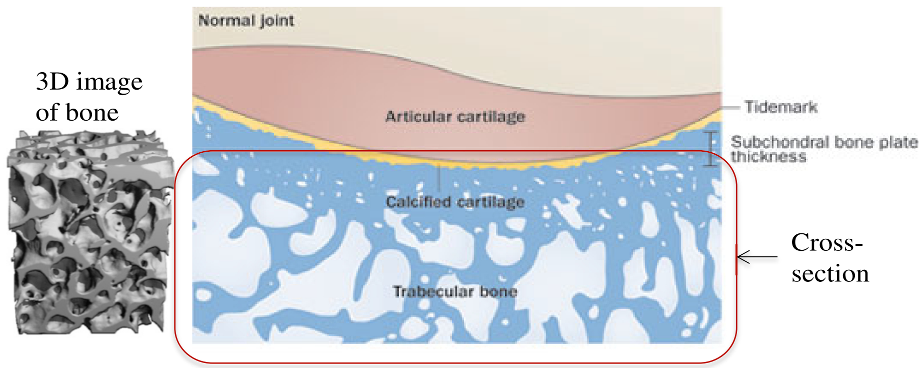
To date, no adequate standard has been developed to quantify such changes. However, Braincon's latest development, the i3A [Ljuhar (2016); Ljuhar *et al.* (2016)], provides a hardware and software solution for predictive diagnosis of osteoarthritis, which, to date, has primarily been applied to the knee. Specifically, the i3A can identify arthritis in its early stages by looking at the surface roughness of bone structure surrounding the knee joint. The i3A consequently helps doctors decide whether a patient needs surgery, pharmaceutical treatment or no treatment at all. The goal is to minimize risk of fracture.

Braincon argues that morphologic changes to the trabecular structure are the missing link for early disease prediction [Ljuhar (2016)]. As Fig. 3 suggests, its i3A approach can identify anomalies in the bone micro-architecture at an early stage. The i3A algorithm investigates the self-similarity of the gray values in an X-ray that represent the trabecular bone structure of the subchondral tibia region. It does so by calculating the Bone Structure Value (BSV), a normalized entropy value that has a range from 0 to 1. A higher BSV is the result of a high grade of self-similarity which can be linked to a stable bone micro-architecture. (For formulae of the BSV and its relationship to Shannon's Entropy [Shannon and Weaver (1949)], please see [Ljuhar (2016); Ljuhar *et al.* (2016); Rocha *et al.* (2008)].

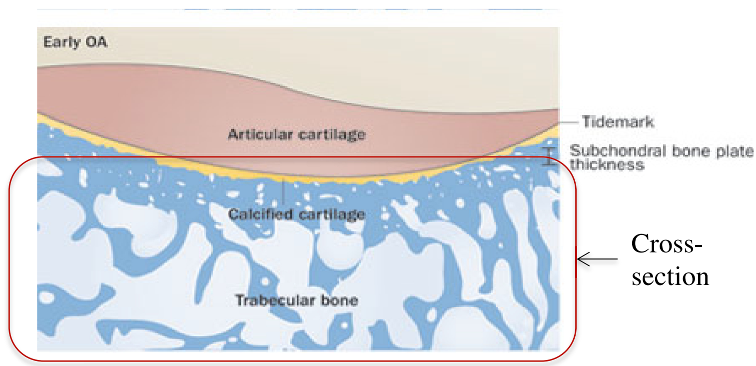
The i3A reduces nescience in a manner that is analogous to the problem-solving practices in the semiconductor industry. Prior to the analysis, one assumes equiprobability, i.e. a BSV of 1. The i3A compares the gray scale value of each pixel to the gray scale values of all adjacent pixels. High differentials in gray scale translate into a concentration of probability, or a low BSV, just like the probability distribution of an electrical fault concentrates around fewer and fewer process steps that become increasingly "suspicious". In both situations, nescience is reduced automatically, i.e. faults are localized by sophisticated diagnostic imaging tools [Schatten *et al.* (2003); Weber *et al.* (2002)].

There are two big differences between the i3A and problem-localization practices semiconductor manufacturing. First, the i3A operates in two physical dimensions, rather than in one virtual dimension. The i3A scans the *surface* of the bone, whereas solving problems in semiconductor manufacturing takes place on a virtual *number line* — the sequence of steps in the manufacturing process. More importantly, scanning the surface of a bone for anomalies constitutes a problem that is so well-structured that Braincon was able to develop algorithms forthe i3A, which automate the trial-and-error processes that lead to the problem's solution [Ljuhar (2016)]. By contrast, yield problems in semiconductor manufacturing and process development tend to be highly ill-structured; their solutions require extensive (and expensive) investigations before trial-and-error procedures can be applied successfully [Weber (2002)].

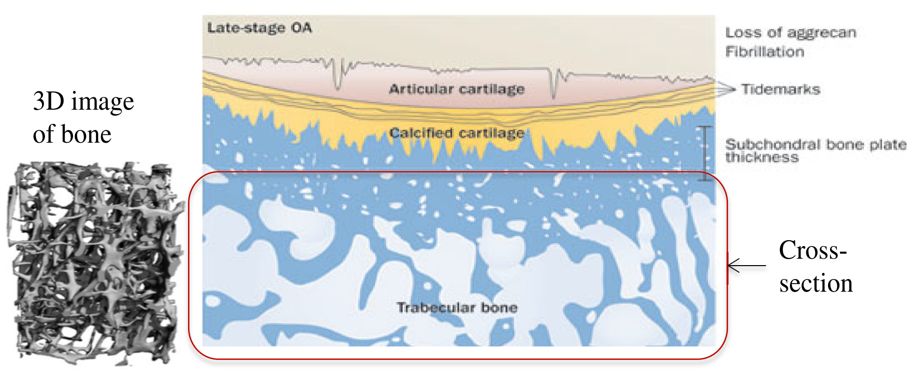
The primary function of i3A is to improve the quality of diagnosis, which allows it to act as a decision aid. Before the i3A was deployed, bones could either be diagnosed as healthy or unhealthy depending on the measurement of bone mineral density. The introduction of the i3A provides the decision makers (diagnostic physicians) with three options: no arthritis, early-stage arthritis and late-stage arthritis. Each of these stages warrants different treatment. No arthritis means no treatment; early-stage arthritis warrants a pharmaceutical approach; late-stage arthritis usually mandates surgery. Thus, the ability to observe osteoarthritis in its early stages using the i3A is enabling the widespread deployment of pharmaceutical approaches. In essence, the i3A acts as an instrument of predictive maintenance. Relying on the information



(a) Normal joint



(b) Early OA



(c) Advanced OA

Fig. 3. The three stages of osteoarthritis (adapted from Ljuhar [2016]).

provided by the i3A allows a physician to prescribe the less invasive pharmaceutical approach, thereby preventing the more intrusive surgery at a later date. Deploying the i3A also reduces the frequency of calamitous false negatives. An incorrect diagnosis of "healthy" on a brittle bone is becoming increasingly rare.

7. Locating Influencers in Online Social Networks

Traditional marketing models are swiftly being upended by the advent of online social networks [Chakrabarti and Berthon (2012); Khammash and Griffiths (2011); Longart (2010)]. Millions of consumers continuously partake in highly fluid conversations in virtual communities on social media platforms like Twitter [Dodds *et al.* (2011)] in which the success or failure of a product or services may be decided [Chakrabarti and Berthon (2012)] by a few key "influencers" that determine the behavior of other actors in the community [Cartwright (1965); March (1955)]. Understanding the structure and behavior of online social networks, as well as identifying the key influencers, may consequently constitute a crucial source of competitive advantage for firms that engage in new product development.

Despite the increasing importance of online social networks, nescience about the phenomenon is widespread. Practicing firms that are engaging with online social networks neither have a reliable theory nor sufficient practical experience to make sense of the phenomenon [Adamic and Adar (2005); Aral and Walker (2011, 2012); Dellarocas *et al.* (2013); Li and Bernoff (2008); Wiertz *et al.* (2010)]. For example, social media analytics firms like Klout, Kred, PeerIndex, and Traackr, who have tried to analyze online social networks by finding the individuals that have the most friends and followers or generate the most output, have not been particularly successful [Cha *et al.* (2009, 2010)]. Evidently, the individuals within a network who have the most connections or generate the most activity online are not necessarily the ones that exert the most influence in social media [Cha *et al.* (2009, 2010)]. In addition, whatever influence they have appears ephemeral [Chen *et al.* (2009)]. Instead, people tend to consume information as they have done in the real world [Rogers (2003)] from people they know and from people they trust [Wolf and Scott (2013)]. Furthermore, extant theory of social networks is based on observations of the real world [e.g. Allen (1977); Bailey (1990); Burt (1992); Cartwright (1965); Coleman (1988); Luhmann (1986); Miller (1978); Parson (1951); Rogers (2003); Tichy *et al.* (1979)] and may thus not apply to online social networks [Mayande (2015); Mayande and Weber (2011)]. Practicing firms may consequently be misallocating a large amount of resources, simply because they do not understand the behavior and organization of the online social networks with which they interact [Edwards (2012, 2014)].

In 2011, Xilinx's management realized that there was a lot about their markets that they did not know, especially when it came to social media. The company hired SMAF to analyze the Twitter conversations about its products, services and technologies. Xilinx hoped that SMAF's analysis would provide feedback on how it (Xilinx) is doing in its existing markets and perhaps identify some new market opportunities.

SMAF deployed a multi-stage approach that utilized information theory to reduce nescience. Key influencers were identified by entropy centrality; entropy centralization quantified the concentration of information within the whole network. First, SMAF recorded all traffic pertaining to Xilinx's Twitter account, @xilinx, for a period of two months — from 01/12/2012 to 03/12/2012. This endeavor reduced

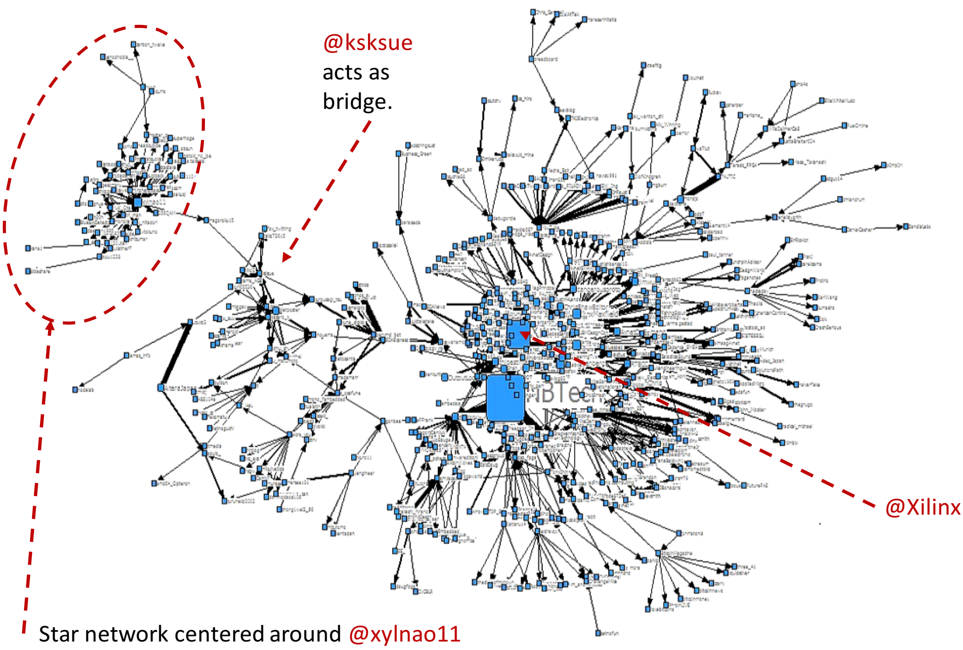


Fig. 4. Visualization of the community that contains @xilinx and @xylnao11.

nescience by identifying a community of 571 accounts (nodes), whose structure is displayed in Fig. 4. (This community communicated a total of 1176 times — 453 @mentions and 723 retweets — within the time it was under observation; each tie in Fig. 4 depicts a relationship that involved at least one @mention or retweet.) This community would serve as the solution space of any subsequent analysis because any node that was neither directly nor indirectly connected to @xilinx could not exert influence on that node. It also turned out that the Xilinx Twitter community was a network that was only moderately active and changed relatively slowly. The number of retweets within the community exceeded forty on one day only. On some days, no communication occurred within the network at all. This is relatively benign for a Twitter community.

SMAF treated the Xilinx community as a directional network by differentiating between the tendency to propagate information and the tendency to consume information. (This can be observed in Fig. 4, where ties are represented as arrows whose direction reflects a net information flow.) SMAF subsequently continued to reduce nescience by generating a network that represents the propensity to propagate information and calculating the information propagation potential for each node in that network using the formula in (3). Table 2 displays the results of this calculation for the 10 nodes with the greatest propagation potential and normalizes the results with respect to the node with the largest propagation potential. Table 2 also ranks the nodes in decreasing order of propagation potential.

Nescience was reduced even further when two nodes — @xylnao11 and @ksksue — sent a strong signal to SMAF's analysts. Both nodes exhibited a very

Table 2. Ranking screen names by propagation potential.

Rank	Screename	Normalized propagation potential
1	***xylnao11***	1.000
2	alteracorp	0.723
3	AvnetOnDemand	0.685
4	dietposter	0.369
5	FPGATechnology	0.240
6	basaro_k	0.174
7	***ksksue***	0.122
8	ee_times	0.110
9	yishii	0.088
10	s_osafune	0.077

high propagation potential, yet neither was connected to particularly many other nodes. SMAF generated the community visualization map in Fig. 4 to interpret these anomalies. The map revealed that neither node was near @xilinx within the network. @xylnao11 was at the center of a star-shaped network; he/she communicated with many other accounts that did not engage with each other. This meant that the community surrounding @xylnao11 would collapse, if he/she were to become inactive. @ksksue was not part of @xylnao11's direct network, but he/she performed an important function for @xilinx, by acting as a bridge between @xylnao11's community and the larger community that surrounded @xilinx. No community would collapse, if @ksksue were to become inactive, but the link between @xilinx and @xylnao11 would be severed.

Due to SMAF's analysis, Xilinx became aware of the existence of the community that surrounded @xylnao11. It also knew how to contact that community. However, Xilinx did not yet know whether it was in the company's interest to do so.

To make that determination, SMAF conducted a semantic analysis of the network in Fig. 4. This analysis produced a frequency count of the words within the Twitter conversations between the various actors within the network in Fig. 4. It also gave SMAF a good idea of who said what to whom on specific dates. SMAF subsequently decomposed the word cloud, trying to identify conversations within @xylnao11's community that could be of interest of Xilinx. In the process, SMAF came up with the word network in Fig. 4, in which @xylnao11's community discussed topics related to Xilinx. Further analysis of the individual tweets within @xylnao11's community revealed that the community comprised a group of automotive engineers in Japan, who were talking about using FPGAs to detect pedestrians through vision sensors. These conversations were definitely of interest to Xilinx, a leading maker of FPGAs, as they constituted a potential market opportunity.

8. Discussion of Findings

Reducing nescience through problem localization has been part of the problem-solving process in semiconductor manufacturing for decades [Weber (2002)], and the ability to quantify nescience has been available for almost 20 years [Weber *et al.* (2002)]. However, the extremely urgent conditions that drive problem-solving in semiconductor manufacturing reinforce the total systems approach to organizational learning that dominates the industry [Weber *et al.* (1995)]. Knowing how close you are to localizing your problem, which is the information that the entropy measure provides, is less important than focusing on localizing and solving the problem itself. Furthermore, projections pertaining to the reduction of entropy are subject to interpretation. Thus, pinning a greater entropy differential on one experiment as opposed another will not necessarily convince management to launch that experiment first. Despite extensive debate about entropy as a metric, the perceived speed with which a problem can be resolved still determines the approach in most semiconductor fabrication facilities [Leachman and Ding (2007); Weber (2002, 2004, 2006, 2013)]. Therefore, the perceived value of utilizing entropy-based metrics to solve yield problems in semiconductor manufacturing is relatively limited. Yield analysis engineers successively localize the source of an electrical fault to a particular process step as a matter of routine problem-solving practice. Entropy decreases implicitly as a consequence; it does not act as a guidepost. And finally, pinning an entropy metric to the degree that a problem is considered localized does nothing to improve the problem's structure. Semiconductor yield problems still contain a significant amount of ambiguity [Weber (2002)], even if the status of the problem-localization process can be quantified.

Entropy-based approaches to managing nescience had a higher perceived value in the medical diagnostics study where the economic environment does not generate a sense of urgency. In the case of Braincon, the quality of a diagnosis was paramount. Identifying the potential locus of a bone fracture clearly outweighed the cost discovering this phenomenon or the speed at which the diagnosis was performed. Furthermore, the diagnosis problem was well-structured, and nescience could be quantified by utilizing entropy metrics. Thus, the i3Awas able to run on automated versions of well-known trial-and-error processes. It acted as a decision aid for physicians, who could prescribe surgery, a pharmaceutical approach or no treatment at all, depending on the outcome of the i3A's analysis. The perceived value of entropy-based metrics was clearly high because they constituted an explicit and integral part of a technological solution that provided the analysis [Ljuhar (2016); Ljuhar *et al.* (2016); Rocha *et al.* (2008)].

The social network analysis study illustrated how approaches based on information theory could help managers cope with nescience by bringing a phenomenon from the unknown unknown to the known unknown. In this study, SMAF was able to identify a virtual community of automotive engineers of which Xilinx was totally unaware. Recognizing the existence of this community allowed Xilinx to develop approaches that could potentially turn this community into customers. Once the existence of the community was known, an approach that partitions the solution space of the problem by trial and error could be attempted, i.e. the problem became well-structured [Baron (1988); Pople (1982); Reitman (1965); Simon (1973); von Hippel (1990)]. Once again, entropy-based metrics were at the core of the technological solution that SMAF provided. They were highly valuable to Xilinx because they identified potential customers to that firm.

Table 3. Comparing the three empirical studies in this paper.

Study	Drivers of success	Problem structure	Perceived value of approaches based on information theory
Semiconductor Manufacturing and Process Development	Yield, Speed, and Capital Productivity	Primarily ill-structured	Limited (appreciated but not in use)
Medical (OA) Diagnostics	Accuracy of Information	Well-structured	Very high–decision aid (at the core of enabling technology)
Social Network Analysis	Availability of Information	Convertible to well-structured	Very high (identifies potential customers for client)

The findings of our investigation illustrate that the perceived value of entropy-based metrics for nescience varies from setting to setting, suggesting that the normative value of the theoretical framework presented in this paper depends upon context. Practitioners valued solutions based on information theory very highly in medical diagnostics [Ljuhar (2016); Ljuhar *et al.* (2016); Rocha *et al.* (2008)] and in social networks analysis, which are respectively driven by the quality of information and its availability. In these settings, entropy-based metrics became part of a technological solution. By contrast, semiconductor manufacturing is driven by yield [Bohn and Terwiesch (1999)], urgency [Leachman and Ding (2007); Terwiesch and Bohn (2001)] and capital productivity [Silverman (1994)]. Approaches to problem solving based on information theory are thus rarely deployed in semiconductor manufacturing, even though entropy-based metrics characterize the problem localization process in that industry quite well [Weber *et al.* (2002)].

It should be noted that practitioners do not use the term nescience in their day-to-day conversations in any of the three studies. Semiconductor yield analysis engineers tend to talk about "localizing the problem"; many of them may not know what the term nescience means. Solution providers in the medical diagnostics study use the term "entropy" quite openly, but their customers, the physicians, do not. Neither group openly discusses nescience. Centrality metrics are at the center of many discussions in social network analysis. However, the term nescience is not. These observations reinforce the notion that practitioners are focused on resolving their particular problems instead of developing generic approaches to problem solving (like those discussed in Baron [1988], Marples [1961], Pople [1982], Reitman [1965] and von Hippel [1990]). Practitioners would consequently have to be educated in how to apply an actionable, generalizable theory of nescience, once such a theory has been developed.

9. Conclusions

This paper has described three studies of how quantifying nescience has facilitated problem solving in high technology settings. In all three studies, variants of Shannon's original entropy formula [Shannon and Weaver (1949)] have acted as a proxy measure for nescience. Therefore, our investigation has demonstrated that information theory can provide a theoretical framework for managing nescience in practical settings. In all three studies, decreasing the entropy of a system was tantamount to reducing nescience by localizing a problem or by shrinking its solution space. In semiconductor manufacturing, the probability of finding a fault was concentrated to a few steps in a process. In the medical diagnostics study, reducing entropy meant increasing the probability of correctly determining the locus of a potential fracture. In the study of social media analytics, reducing entropy centrality and entropy centralization respectively help determine the loci and regions of influence online. These findings lead to the conclusion that the descriptive value of the theoretical framework proposed in Sec. 3 of this paper is rather high.

The three studies presented in this paper constitute a response to a general scarcity of applied research pertaining to nescience. They must be considered exploratory due to research methods that were deployed and because a sample of three settings is rather small. Thus, the generalizability of these studies is limited. However, the studies transpired in settings that were chosen for their contrasting economic environments. Entropy metrics were shown to be potentially applicable to all three settings and in active use in two out of three studies, suggesting that at least some degree of generalizability can be ascribed to the findings of this paper.

The observations in all three studies lead to the conclusion that the theoretical framework presented in this paper is a highly pragmatic one. Approaches to reducing nescience that can be derived from information theory tend to be deployed in settings in which the quality of information and the availability of information are of critical value and problems tend to be well-structured (see Table 3). Thus, the efficacy of the framework may be limited to such settings. It may be less applicable in settings that are driven by other factors. This outcome is considered acceptable from the point of view of pragmatism, which has little concern for universal truths [Spender (1996, p. 49)]. However, generalizing the framework in this paper toward a more broadly-based theory of nescience would involve more empirical research that tests information-theory-based approaches in additional settings in the industries under study in this paper or in others.

Finally, it should be noted that nescience implies absence of knowledge rather than absence of information and that entropy is a measure of information rather than knowledge. As Weber and Mayande point out, "... knowledge is more than information. It is information that is sufficiently certain [Shannon and Weaver (1949)] and sufficiently contextualized to enable human action [Stehr (1992)]." [Weber and Mayande (2017, p. TBD)]. Thus, the authors of this paper do not necessarily conclude that entropy-based measures provide the best theoretical framework for managing nescience. Attempts to build a more general theory of nescience (such as those being conducted by García-Leiva [2018] and Klein [2001]) could consequently make significant contributions to understanding the phenomenon of nescience and provide significant value to practitioners. These endeavors will hopefully stimulate further empirical studies through which evolving theories of nescience can be validated.

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